Using landscape structure to classify grizzly bear density in Alberta Yellowhead Ecosystem bear management units

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Abstract: Landscape metrics derived from a Landsat-5 Thematic Mapper (TM) satellite image classification of landcover were used to quantify the structure of grizzly bear (*Ursus arctos*) habitat within bear management units (BMUs) in the Yellowhead Ecosystem in west-central Alberta, Canada. Statistical relationships were developed using 3 bear density classes that were based on DNA data obtained in 1999 from 192 hair snagging stations distributed within 9-km^2 grid cells. The relative differences among the available 16 BMUs were quantified and interpreted using 4 landscape metrics (edge density, mean patch size, mean-nearest-neighbor, and patch size covariance). Using discriminant functions, greater than 80% accuracy was achieved with these metrics in classification of BMUs with low, medium, and high bear density classes. BMUs with higher bear density had both lower edge density and greater mean patch size; BMUs with lower bear density had greater patch size covariance and mean nearest neighbor distance.

Key words: Alberta, bear management, density estimation, discriminant function, grizzly bear habitat, Landsat image, landscape metrics, *Ursus arctos*

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Grizzly bear management units (BMUs) in the Yellowhead Ecosystem of west-central Alberta, Canada, have high ecological, social, and economic values (Stenhouse and Munro 2001). Models that quantify the amount and distribution of human activity that potentially limit bear presence, density, and behavior must be developed and tested in such areas for input to the management process (Boyce and McDonald 1999). Different aspects of bear populations, such as abundance, density, or distribution, may be related to landscape structure, quantified using landscape metrics that are developed for general application or for a particular species–habitat relationship. Landscape metrics are computations that describe total landscape area, diversity of patch types within the landscape, and various aspects of the patches themselves, such as their size, shape, variability in size and shape, distance between patches of the same type, and the degree to which patch types are isolated (Forman and Godron 1986, McGarigal and Marks 1995). In previous research, such landscape metrics have been applied in habitat analyses of the distribution of birds and mammals (Andren 1994, Dijak and Thompson 2000). Studies of timber wolves (*Canis lupus*; Mladenoff et al. 1995) and American marten (*Martes americana*; Chapin et al. 1998, Hargis et al. 1999) have adopted multivariate statistical techniques, such as regression, to develop predictive models of the influence of landscape structure on wildlife populations.

We hypothesized that a similar approach could help explain some aspects of grizzly bear populations in the Alberta Yellowhead Ecosystem. For example, based on earlier, largely anecdotal, observations of bear density in this region (G. Stenhouse, unpublished data), it was suggested that certain BMUs (ones with fewer disturbance patches, larger intact forest areas, lower edge density) may have higher bear densities. To test this idea, we interpreted selected landscape metrics obtained from a satellite image classification map to identify differences in BMUs with different estimated bear density. We used the satellite image landcover classes to interpret bear habitat. A discriminant function analysis was used to determine the ability of the selected metrics in classification of low, medium, and high bear density classes. The main purpose of the discriminant

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function analysis was to identify along which dimensions (comprised of variance in specific landscape metrics) these bear density classes differed and to predict BMU bear density class membership through classification (Tabachnick and Fidell 1989). If significant differences among BMU bear density classes were measured using the landscape metrics, then discriminant functions can classify the density class (i.e., low, medium, or high density) to which each BMU belonged. The discriminant function was developed using training data, which were also used as a limited test of the explanatory power and accuracy of the function. Ideally, independent training areas are required to examine or verify discriminant function performance (Klecka 1980). Therefore, we developed the discriminant functions using a randomly selected number of BMUs and tested the functions using the remaining BMUs.

Study area and data collection

Sixty-nine percent of the current range of grizzly bears in the province of Alberta occurs in the Yellowhead Ecosystem region (Alberta Environmental Protection [AEP] 1990; Fig. 1). This area also contains Jasper National Park, industrial forestry management agreement areas, town sites, mines, transportation corridors, recreational areas, and oil and gas exploration and developments. The Yellowhead Ecosystem includes the high relief of the Rocky Mountain Eastern Main and Front Ranges in the west and the rolling foothills in the east (GEOWEST 1997). The topography, developed on sedimentary rocks, ranges from 950 to 3,400 meters above sea level and is controlled by the Rocky Mountain Thrust Belt, resulting in northwest to southeast oriented ranges. The uplands are dissected by glacier-fed rivers and streams that generally drain to the northeast. The area contains glacial erosion and deposition features and moderately to poorly drained soils developed on sand, lacustrine clay, discontinuous glacial till, and some organics. The mixture of vegetation species depends on site history and geographical location (Strong and Leggat 1992). Within the forested ecoregions, fire regime and moisture availability determines the dominant vegetation communities. At lower elevations in seeps or standing water, wetlands dominated by black spruce (*Picea mariana*), willow (*Salix* spp.) and birch (*Betula* spp.), or sedge (*Carex* spp.) complexes occur. Fire-successional lodgepole pine (*Pinus contorta*) dominate the low to mid-elevations (approximately 1,000 m) due to natural historic fire occurrence. White spruce (*Picea glauca*), Engelmann spruce (*Picea engelmannii*), and subalpine fir (*Abies lasiocarpa*) are also common at mid-elevations in the subalpine. Above the tree line, heather (*Phyllodoce* spp.), willow, and white mountain avens (*Dryas octopetala*) are the prevalent vegetation species of the alpine ecosystems.

Methods

Approximately 5,500 km^2 of the Yellowhead Ecosystem was delineated according to watershed boundaries into 16 bear management units (BMUs; Fig. 1). These BMUs were created to allow evaluation of existing grizzly bear cumulative effects models (Purves and Doering 1998); the units approximate the size of an average female grizzly bear's home range in this region (300–400 km^2) and are considered appropriate by regional land managers interested in assessing the effects of resource industry activities on grizzly bear habitat (Stenhouse and Munro 2001). DNA data were collected from scented hair snagging stations in 1999 following techniques presented by Woods et al. (1999). Three of these hair-snagging stations were placed in each of 64 nine-km^2 grids for 2-week durations. Over the course of a 6-week sampling period, hair was collected from these stations; subsequent laboratory analysis was performed (Paetkau and Strobeck 1994) to identify species and gender and microsatellite analysis conducted to differentiate individual animals. Results of these analyses provided a study area population estimate; however, for the purpose of the present analysis we worked at the grid cell sampling scale within each BMU. This was accomplished by tallying the number of individual grizzly bears captured by hair snagging within each grid cell during the sampling period. These data were scaled up from the grid cells to the BMUs by simple averaging, which provided a relative bear density class (Fig. 1) for each BMU. The relative bear density classes were grouped into arbitrarily defined low (0–3 bears), medium (4–6 bears), or high (7–9 bears) density. The low density class comprised 6 of the BMUs, and the medium and high density classes each comprised 5 BMUs. No population estimates of bears are associated with the density classes within each BMU.

A Landsat-5 Thematic Mapper (TM) image classification map was produced to show landcover and grizzly bear habitat distribution in the study area (Fig. 2; Franklin et al. 2001). A supervised decision-tree classification method based on >250 field training areas was employed. The input variables were the tasseled cap transformation (TCT) components of brightness, greenness, and wetness (Crist 1985) plus geomorphometric

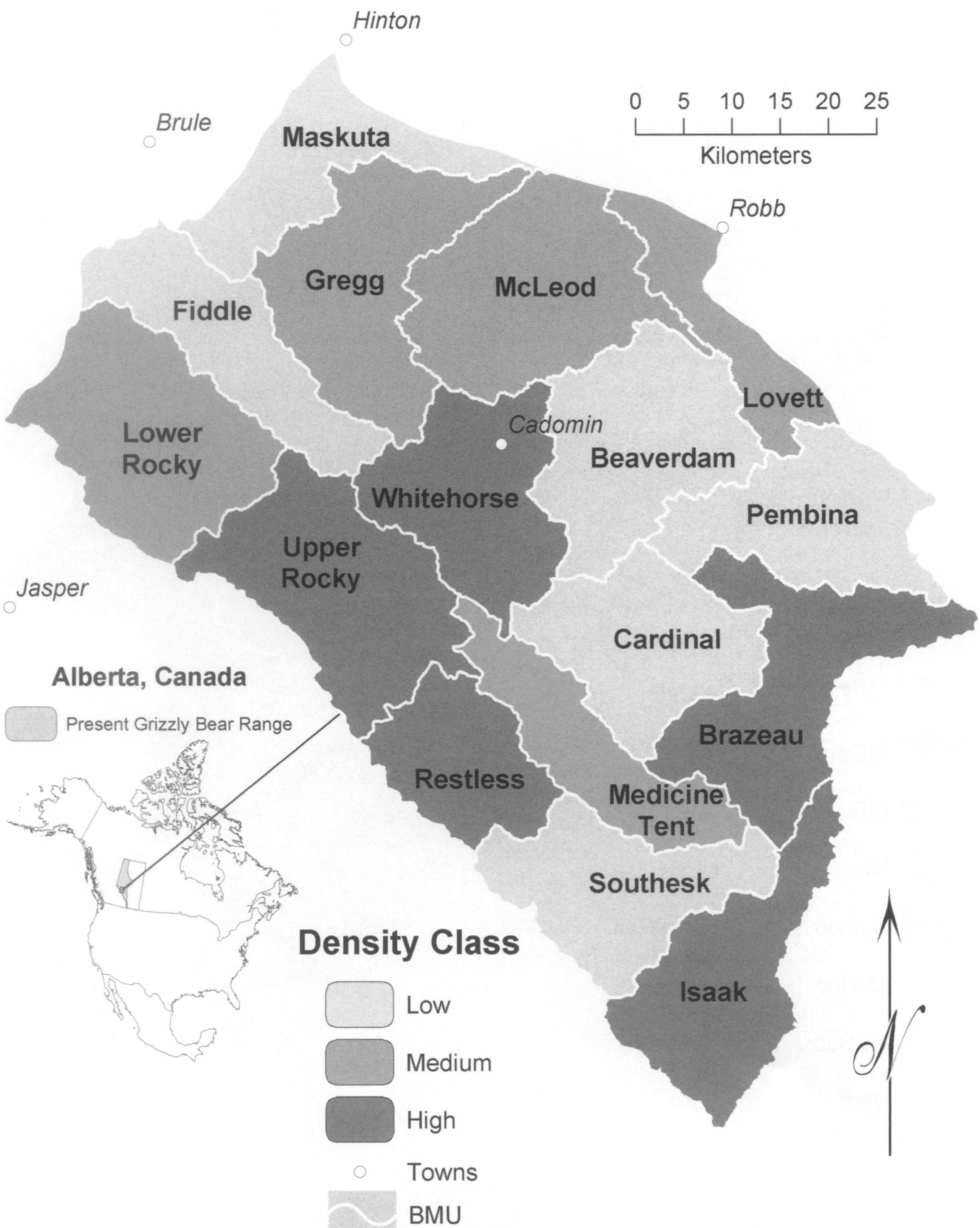

Fig. 1. Location of study area in west-central Alberta, Canada, 16 bear management units, and relative grizzly bear density estimates, 1999.

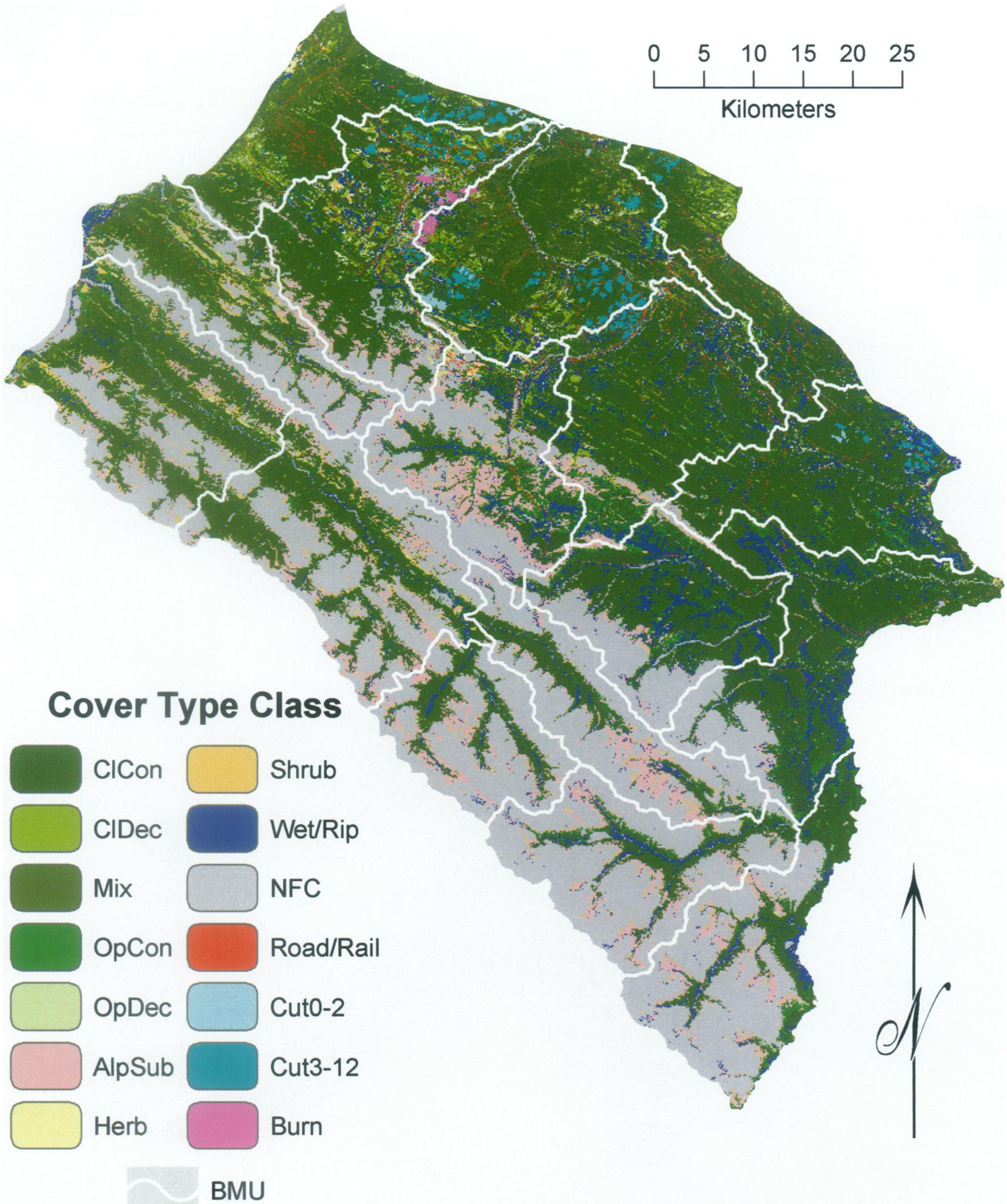

Fig. 2. Satellite image land cover classification used as input to landscapes metric calculations for study area in west-central Alberta, Canada, 1999 (Franklin et al. 2001).

variables (such as slope) extracted from a digital elevation model (Franklin 1987). GIS-based rules were used to help define some of the classes (e.g., riparian shrub). The final map accuracy was determined to be approximately 83% correct at >400 locations interpreted on digital orthophotographs and in the field. This raster map was used as input to the landscape metric calculation procedure using the patch analyst extension to ArcView 3.2 (Elkie et al. 1999).

The power of different landscape metrics to discriminate landscapes was tested using the 16 available BMUs. Unfortunately, the low number of BMUs available precluded more comprehensive tests, but the use of these discriminant functions provide an indication of the suitability of the classification variables (i.e., the landscape metrics) in identifying and separating bear density classes at the scale of the BMUs.

First, we used a 12-variable combination of the metrics thought to contain measures that accurately summarized the differences in the BMUs that could be interpreted visually on the map products (Table 1). Included were measures of landscape area, number of patches, mean patch size, edge statistics, and distance measures. All metrics were entered into the discriminant analysis using both forward and backward selection. The discriminant functions were tested for variable tolerance. We interpreted the functions for significant explanation by metrics. Based on these results, a second test was conducted using a set of fewer (8) landscape metrics. Several metrics, for example the mean patch fractal dimension (MPFD), were omitted due to the apparent complexity in interpreting the patterns. The remaining metrics were used to develop and test a discriminant analysis function in which 6 randomly-selected BMUs were, in turn, omitted or 'held-out' from the development and accuracy assessment of the function. We interpreted the resulting classification accuracy as a measure of how well these landscape metrics can separate BMUs with different bear density estimates.

Table 1. Landscape metrics selected (from map interpretations) to develop discriminant functions to separate 16 Alberta Yellowhead BMUs according to bear density estimates obtained from DNA samples at 64 hair-snagging stations in 1999.

Landscape metrics (units)	Abbreviation
Total landscape area (ha)	TLA
Number of patches	NUMP
Mean patch size (ha)	MPS
Patch size coefficient of variance	PSCOV
Patch size standard deviation	PSSD
Total edge (m)	TE
Edge density (m/ha)	ED
Mean shape index	MSI
Area weighted mean shape index	AWMSI
Mean patch fractal dimension	MPFD
Mean nearest neighbor (m)	MNN
Landscape proximity index	LPI

Results

Based on the discriminant function weights for each input metric (Table 2), the first discriminant function was interpreted to be comprised of variance in the edge density (ED) and mean patch size (MPS) metrics. Graphically, the first discriminant function separated BMUs with high bear density from BMUs with estimated bear densities that were low and medium (Fig. 3). The second discriminant function appeared to separate BMUs with low bear density from BMUs with medium bear density. We interpreted this function as being comprised of the landscape metrics mean nearest neighbor (MNN) and the patch size covariance (PSCOV). Therefore, BMUs that contained both lower ED and greater MPS had higher bear density; BMUs with greater PSCOV and MNN had lower bear density. These 2 discriminant functions resulted in 93.8% of the original BMUs being correctly classified.

Repeated random selection and discrimination of 6 BMUs held-out (i.e., not used in development of the functions) achieved >80% accuracy in all tests (Table 3). This is an independent accuracy assessment that indicates that the discriminant functions are significant and that the selected landscape metrics appear to capture structural differences among the BMUs in each of 3 bear density classes. These differences were expressed in the 4 metrics of edge density, mean patch size, mean nearest neighbor, and patch size covariance. Overall, with the possible exceptions of total land area (TLA) and the interspersion/juxtaposition index (IJI), there were no other clear trends of specific landscape metrics in relation to the density classes. Larger landscapes with greater patch adjacency were expected to support higher bear densities; these 2 metrics had low correlation with either discriminant function.

Discussion

Reasonable discrimination results were found using selected landscape metrics derived from the satellite image classification map to classify relative bear densities by BMU. One interesting BMU was Fiddle (Fig. 1), a low bear density BMU adjacent to Jasper

Table 2. Structure matrix of correlations for each discriminant function, the metric variables, and the associated means and standard deviations per density class (n = 16) using metrics from Table 1.

Structure matrix function			Bear density class means and SD					
			1 – Low		2 – Medium		3 – High	
1	2	Metric	Mean	SD	Mean	SD	Mean	SD
0.295[a]	−0.216	ED (m/ha)	94.57	25.01	109.48	30.37	81.83	20.11
−0.186[a]	0.183	MPS (ha)	5.22	2.70	4.14	2.18	5.80	1.56
0.032	0.397[a]	MNN (m)	99.70	11.77	91.20	5.44	94.50	7.65
0.203	−0.276[a]	NUMP (#)	7,242.83	3,057.43	9,893.60	5,254.04	6,549.40	2,467.20
0.034	0.251[a]	PSCOV	2,888.08	955.64	2433.09	700.97	2582.23	505.32
0.082	0.144[a]	AWMSI	8.26	1.85	7.66	1.91	7.54	1.71
−0.101	−0.127[a]	TLA (ha)	31,683.78	4,071.75	33,955.69	11,255.12	35,056.48	7,708.73
−0.058	−0.094[a]	IJI	69.74	7.68	71.28	7.00	71.68	6.78

[a]Largest absolute correlations between each variable and any discriminant function.

National Park. The DNA hair-snag results may have under-estimated the bear density for this landscape (G. Stenhouse, unpublished data). Based on the landscape metrics measured in this BMU, the discriminant function predicted high or medium bear density.

Another important issue is the natural versus anthropogenic disturbance as contributors to landscape metrics; no distinction was made in this study of these differences, nor was the initial state of landscape structure considered.

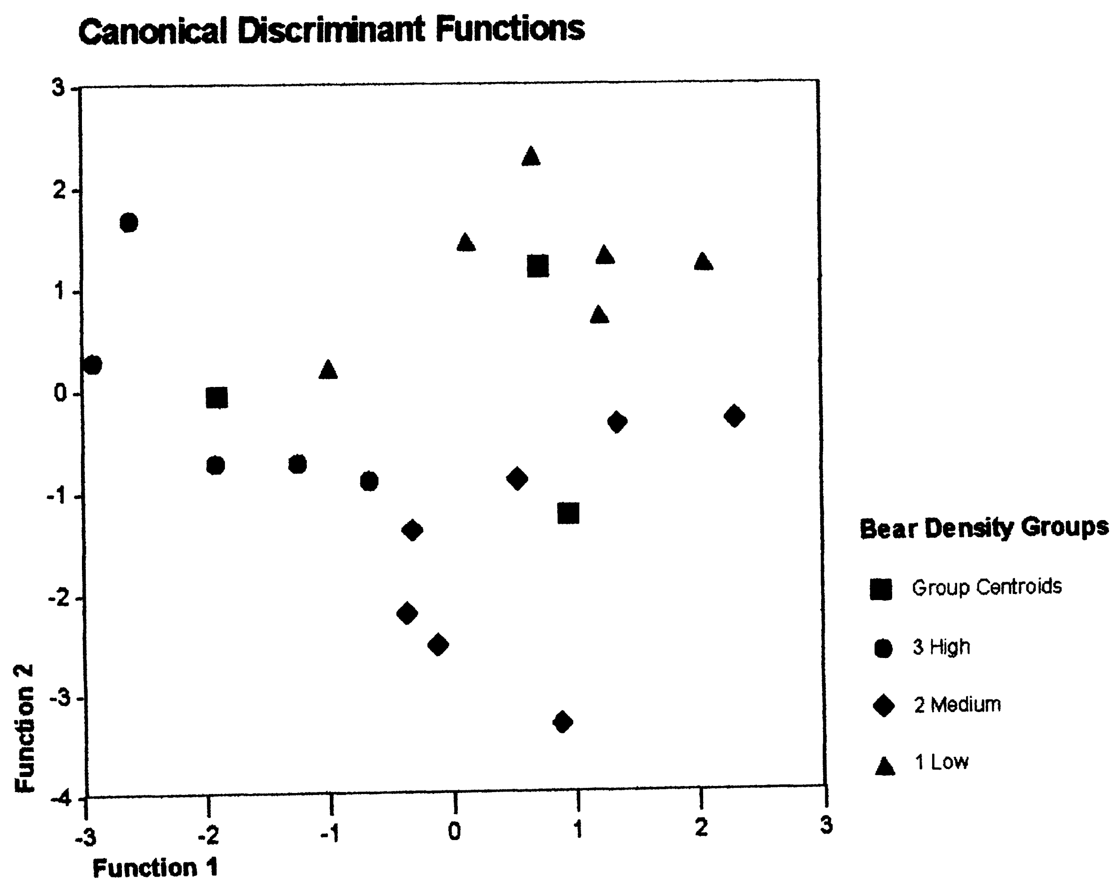

Fig. 3. Scatter plot of discriminant functions with centroids of bear density estimates (high, medium, and low classes) for study area in west-central Alberta, Canada, 1999.

Table 3. Classification accuracy using discriminant functions from several runs with data from 10 randomly selected BMUs applied to the remaining 6 BMUs using selected metrics (edge density, mean patch size, mean nearest neighbor, patch size covariance).

Classification accuracies: independent tests Select random 10 of 16 (6 BMUs tested)	Accuracy (%) $n = 6$	 $n = 10$
Run A (tested Maskuta, Pembina, Gregg, Isaak, Fiddle, Upper Rocky)	100.0	80.0
Run B (tested Fiddle, Upper Rocky, Beaverdam, Lovett, Southesk, Restless)	83.3	80.0
Run C (tested Beaverdam, Lovett, Southesk, Isaak, Medicine Tent, Brazeau)	83.3	100.0
Run D (tested Beaverdam, Medicine Tent, Brazeau, Upper Rocky, Maskuta, Whitehorse)	100.0	100.0
Average	91.7	90.0

These results should be interpreted cautiously because it is known that cover type or patch definition can strongly influence landscape metric variance and that bear population responses to landscape patterns are not yet sufficiently well documented to attribute causal effects. The generalization of the bear density data from the hair snagging stations in 9-km^2 grids to watershed BMUs suggests that the discriminant functions are more useful for land management applications (potential bear numbers) than directly for wildlife management (actual bear numbers) because there were no actual population counts associated with the classification model. The discriminant results could be used to suggest possible future changes in bear density classes with additional human disturbances; also, it may be possible to suggest ways to locate planned activities so as to minimize changes in overall landscape pattern. In future work, a higher number of sampled BMUs will enable more robust testing of the classification model to predict bear density and perhaps other variables of interest, such as bear population abundance and distribution.

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